RediCN: *Reward and disinhibition driven learning in a cortical network*

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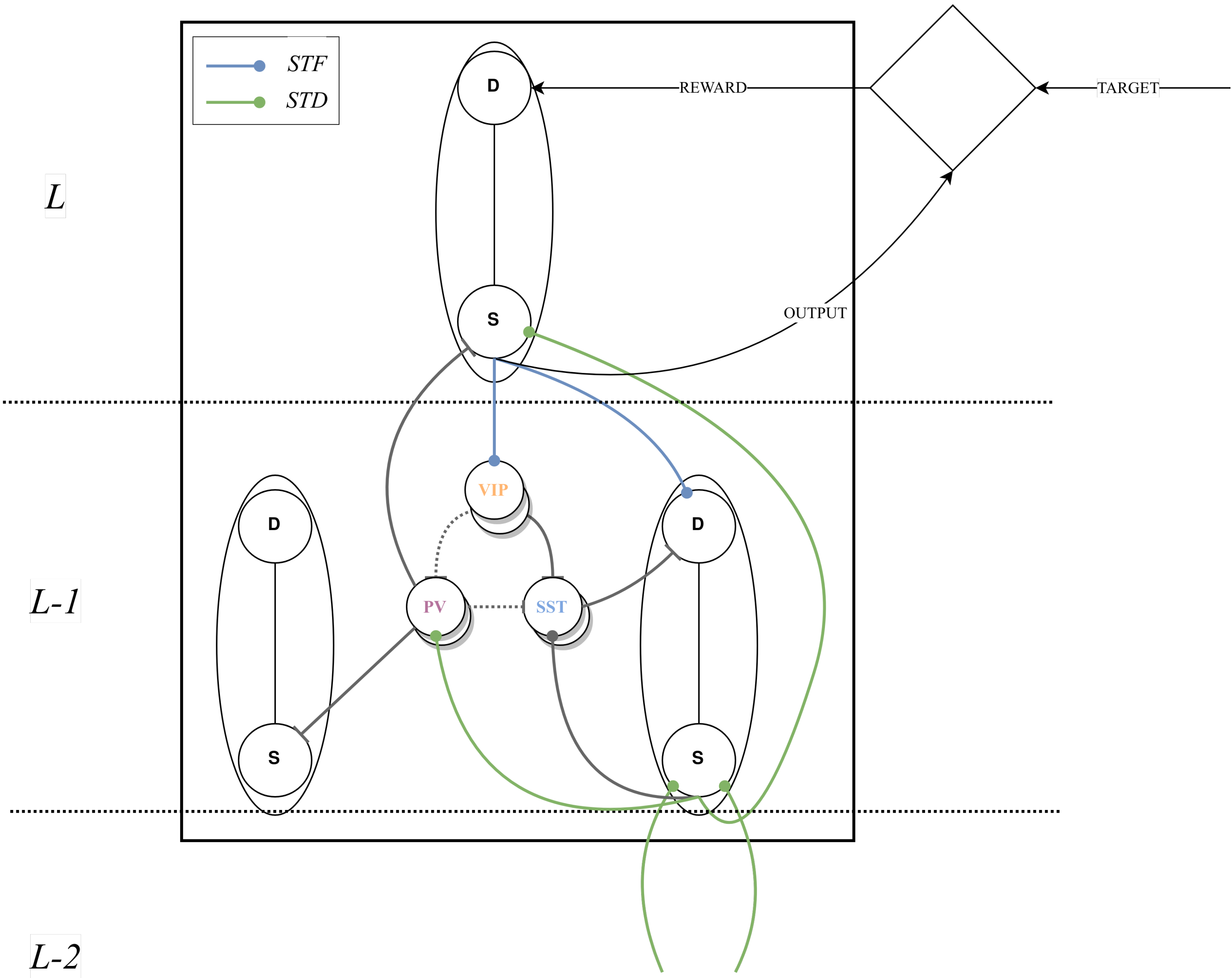
Abstract

Building upon previous foundational work, we combine reward, disinhibition, and multiplexed coding ideas to propose reward and disinhibition driven learning in a cortical network (RediCN). A novel cortical micro-circuit architecture for spiking neural networks (SNNs) that approximates the backpropagation of error algorithm (BP). This network incorporates biological interactions commonly found in the cortex that have yet to be jointly exploited in the context of SNN learning. First, we adopt a multiplexed neural code that combines burst-dependent and short-term plasticity rules to separate bottom-up from top-down inputs and induce learning (*Sacramento et al., 2017; Payeur et al., 2021; Greedy et al., 2022*). In addition, we consider lateral somatic inhibition to aid the suppression of neighboring neurons within the network and, hence, favor intra-layer competition (*Naka & Adesnik, 2016*). Furthermore, inspired by a viable candidate for sensory gating in the cortex and elsewhere, we introduce dendritic disinhibition for guiding the learning process in a fine-grained manner (*Letzkus et al., 2015*; *Wang & Yang et al., 2018; Hertäg & Sprekeler, 2020; Keller et al., 2020, Shen et al., 2022*). Last but not least, based on studies that show prevalent correlations between learning, disinhibition and reward-driven activity at apical dendrites, we use reward as a BP teaching signal for assigning credit to the somatic inputs (*Lacefield et al., 2019; Doron et al., 2020; Pozzi et al., 2020; Schoenfeld et al., 2021; Benezra et al., 2021; Szadai et al., 2022*).

Problem

Learning through credit assignment in a SNN.

Architecture



Notes:

1. Short-Term Facilitation (STF, **blue**) connections carry bursts, while Short-Term Depression (STD, **green**) connections carry events. Plasticity applies only to the latter (*Payeur et al., 2021*)
2. PV, SST and VIP positive interneuron nodes represent populations. Dotted connections represent *weak* inhibition

Learning algorithm

1. Layer *L-1*: Feed-forward, bottom-up input from layer *L-2* arrives at **S** and proportionally excites:
   a. **SST** → inhibit **D**
   b. **PV** → inhibit other **S**
   c. **S** at layer *L*

2. Layer *L*: The output signal $\boldsymbol{O}$ is compared to the target signal $\boldsymbol{T}$, producing a reward signal $\boldsymbol{R}$ that signifies "*Reward the previous layer by this much*":

$$\boxed{\begin{gathered}\boldsymbol{R} = \boldsymbol{R}_{\mathrm{MAX}} - error \\ error = |\mathbf{O} - \mathbf{T}| < \boldsymbol{R}_{\mathrm{MAX}}\end{gathered}}$$

3. Layer *L*: $\boldsymbol{R}$ is fed to **D** as top-down, feed-back input. This signal causes bursts at **S** that propagate to layer *L–1*'s:
   a. **VIP**
   b. **D**

4. Layer *L-1*: Bursts at:
   a. **VIP** (3a) → inhibit **SST** → disinhibit D (*gate open*):
      allows the reward signal to pass with more ease.
   b. **D** (3b) → bursts at **S** → excite **SST** → inhibit **D** (*gate closed*)*:
      allows the reward signal to pass with less ease (leads to 1a).

5. Layer *L-1*: Bursts at **S** → plasticity at its incoming synapses (from layer *L-2*) according to *BCM*-like, post-synaptic, long-term plasticity rule (*Payeur et al, 2021*):

$$\boxed{\Delta W = a(p_{\mathrm{post}} - \bar{p}_{\mathrm{post}})\mathrm{e}_{\mathrm{post}}\mathrm{e}_{\mathrm{pre}}}$$

a: learning rate
p: burst probability
$\bar{p}$: time-averaged burst probability
e: event rate

6. Layers *L-n* ($1 < n < L$): The process repeats, allowing the reward bursting signal to propagate to lower layers and tune inputs there, accordingly.

* When receiving bursts, **SST**'s excitation might need to always exceed its inhibition in order to account for more optimal burst transmission unto **D** (à la *disynaptic inhibition*; see Fig. 7 of Naud & Sprekeler, 2018)

Future modifications

Aspects of this project, such as the following, might require modification in order to mitigate unwanted results arising during implementation, simulations and testing:

- Inhibitory populations connectivity
- Reward signal calculation
- Plasticity rule

Ideas for further differentiation

- Apply reward signal to **many** dendritic compartments (separately or concurrently), instead of just to the output layer ones
- Introduce inhibitory plasticity (e.g. for SST interneurons)
- Investigate and interpret the effects of many dendritic compartments on learning

Action plan

1. Implement proof of concept
2. Demonstrate its capability to learn a basic XOR task
3. Demonstrate its capability to learn a simple non-linear regression sinusoidal wave matching task
4. Demonstrate its capability to learn a simple MNIST task
5. Parameterize, tune and optimize it to improve performance
6. Interpret the results

Implementation candidates

- *Brian2 + dendrify* (*Pagkalos et al., 2022*)
- *PyTorch*

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